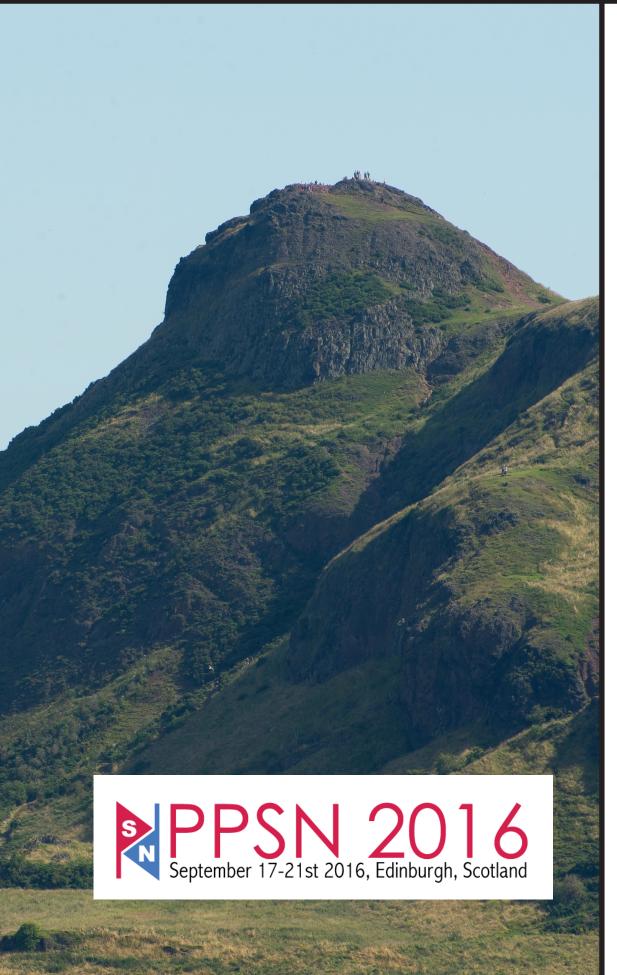
SIGEVOlution

newsletter of the ACM Special Interest Group on Genetic and Evolutionary Computation

Volume 9 Issue 3



in this issue

PPSN 2016

Evostar 2017

An Ethnography of Genetic Programming

Fun and Games at IEEE WCCI 2016

Editorial

Welcome to issue 9/3 of the SIGEVO newsletter! In this we are delighted to present an article by Dr Richard Forsyth, who takes a participant-observer's look back at the genealogy of the computational method now known as Genetic Programming (GP for short) and charts the march of GP from margin to mainstream. The article provides some interesting history for all those who use the technique across a plethora of applications today.

The issue also marks the end of a busy conference season, with a review of PPSN 2016 in Edinburgh, including a statistical analysis of some of the data associated with the conference. I particularly draw your attention to the PPSN author network, produced by Gabriela Ochoa, Nadarajen Veerapen and Fabio Daolio from the University of Stirling, which connects authors across the entire 28 history of the PPSN conferences, and can be examined at your leisure using an interactive version provided online. Bill Langdon provides us with a detailed look at WCCI 2016 for those who were unable to attend both GECCO and WCCI in the summer, and we also look forward to EvoSTAR 2017, kicking off the next conference season in April in Amsterdam. Get writing those papers for the November deadline!

Many thanks to the all the people who contributed to this issue - if you are inspired to write your own article, please get in touch!

Emma Hart

Call for Papers

IEEE Transactions on Emerging Topics in Computational Intelligence Special Issue on "Emergent Topics in Artificial Immune Systems" http://staff.ustc.edu.cn/~wjluo/professional/tetci-ais-2016.html

Topics of interest include, but are not limited to:

- 1. Artificial immune systems for cyber-security: system security, network security, information assurance, authorization, secure cloud computing, secure multi-party computation, fraud detection, big data security, data privacy, privacy-preserving data mining, privacy-preserving data publishing, sensitive data collection, etc.
- 2. Artificial immune systems for fault tolerance: fault prediction, fault detection, fault diagnosis, fault recovery, on-line detection and recovery, fault-tolerant embedded systems, fault-tolerant middleware, survivable techniques, robotics, etc.
- 3. Artificial immune systems for self-organization and adaptation: self-organizing computing systems, foundational models of self-organizing behaviors, networking models and techniques for self-organizing systems, applications of self-organizing systems, autonomic computing, etc.

Important Dates

• Initial Paper Submission: December 31, 2016

• Initial Paper Decision: March 1, 2017

Revised Paper Submission: April 1, 2017

Final Decision (Reject/Accept): May 1, 2017

Publication Date (Provisional): June, 2017

Guest Editors:

- Wenjian Luo, University of Science and Technology of China, wjluo@ustc.edu.cn
- Emma Hart, Edinburgh Napier University, e.hart@napier.ac.uk
- Mengjie Zhang, Victoria University of Wellington, mengjie.zhang@ecs.vuw.ac.nz

THE GENESIS OF GENETIC PROGRAMMING: A FRONTIERSMAN'S TALE

Richard S. Forsyth

http://www.richardsandesforsyth.net/

Abstract

This article takes a participant-observer's look back at the genealogy of the computational method now known as Genetic Programming (GP for short). In so doing, it treats GP as a case study for elucidating the process of technical innovation. Working on the assumption that the contrast between sudden Eureka and stepwise improvement is a polarity rather than a sharp dichotomy, it introduces a simple technique for identifying the main steps in the march of GP from margin to mainstream. It is argued that this approach could be applied more widely to other areas of scientific or technological advance -- possibly even offering the prospect of resolution to some of the more belligerent academic-priority disputes.

Phraseological Preamble

Genetic Programming (also GP) will be familiar to most readers of this journal, both as a family of computational techniques and an academic discipline concerned with studying, extending and applying such techniques. This article is an account of the history of GP from genesis to maturity which endeavours to highlight some of the less well known aspects of that history.

This de-familiarization process begins with the name. I suppose that many readers see nothing strange in the fact that GP refers to a topic that gets discussed at conferences attended by computer scientists rather than biologists. Yet the earliest usage of the term "genetic programming" I could find using Google was part of the following extract.

"The consequence of the ensuing encounter with the impinging multifactored environmental complex may be death, as the inevitable outcome of inadequate genetic programming; or it may be survival, with the genes then co-operatively spelling out the individual developmental tendencies." -- Joranson, P.N. Pulp and Paper Magazine of Canada, 59, 1958, p. 193.

Here it is clear that the term refers to the programming of an organism's development by its genotype -- viewing **genotypes** as **programs**. To me this seems a very natural way to interpret the phrase.

Under another plausible interpretation, arguably also more natural than the one that is now widespread among computer scientists, the phrase would refer to the deliberate programming of actual genetic material. This has recently moved from science-fictional speculation to the realm of practical biotechnology, with the likes of Craig Venter creating synthetic microbes from laboratory-assembled components.

Of course, in our field, we consider GP to be a form of computational search applied to structures that can be executed as computer programs, optimized using a simplified analogue of Darwinian evolution. The Wikipedia entry (ranked first when I typed the term into Google) puts it as follows.

"genetic programming (GP) is a technique whereby computer programs are encoded as a set of genes that are then modified (evolved) using an evolutionary algorithm." -- Wikipedia, accessed 25 August 2016.

We accept a meaning that considers **programs as genotypes**. Thus we are stuck with what I believe an educated outsider would regard as a third-choice interpretation of the term, but it is too well entrenched now to dislodge.

Having established our field of discourse, I would like to offer my preferred definition of GP, that of Bäck et al. (1997).

"Genetic programming applies evolutionary search to the space of tree structures which may be interpreted as computer programs in a language suitable to modification by mutation and recombination." Bäck, T., Hammel, U. & Schwefel, H-P. (1997). IEEE Transactions on Evolutionary Computation, 1(1), 3-17. [emphasis mine]

Since 1997, the idea of expressing GP results as tree structures has been generalized, for example, to linear and heterarchic structures (e.g. Miller & Thomson, 2000), while retaining the essential aspects of tree structures, namely variable length and multiple levels.

Who, When and How?

GP in this sense is today an established academic field, with numerous conferences, journals and research groups. It is instructive to chart its history, from emergence to acceptance, which, in my view, illuminates some important issues in the process of scientific and technical innovation.

It is no secret that priority is a hotly coveted prize among scientific researchers. To be the first to devise, discover or invent something that becomes widely accepted is a high form of success. It leads to kudos, promotion and respect from colleagues and peers. Therefore priority disputes are common, dating back at least as far as Newton's quarrels with Hooke and Leibniz. Most such disputes are eventually resolved by a creeping consensus that settles on a single party in the debate, at least as far as the textbooks are concerned.

For example, scholars may publish articles in learned journals that examine the diverse formulations by a handful of chemists in the nineteenth century (such as Newlands and Meyer) who devised tabulations exhibiting patterns of relationship among chemical elements; but for the purposes of educating chemistry students or explaining the field to the wider world there was just one originator of "the" periodic table, namely Dmitri Mendeleev. Moreover, its inception can be dated to a single day, 17 February 1869, after apparently coming to Mendeleev in a dream (Scerri, 2011).

This is how we like our scientific history, in legendary style, with a single hero on a single date breaking through from darkness into light. The dream is optional, though it does help to have a quirky detail to make the story memorable.

The classic of this type is the "Eureka Moment" of Archimedes in his bath, or rather jumping out of it once he had worked out how to measure the density of a golden crown, which according to the legend turned out to be an alloy of gold and silver.

Other legendary examples include Galileo dropping balls from the top of the leaning tower of Pisa, Newton watching an apple fall in his mother's orchard and Kekulé realizing the structure of the benzene molecule after a reverie on the upper deck of a horse-drawn bus about a snake eating its tail.

It is quite possible that all four of these famous Eureka Moments are apocryphal, but they do a good job of presenting scientific innovation as a sudden flash of insight. Very much in the same spirit is the following quotation from Popular Science (Keats, 2006).

Picture credit: https://commons.wikimedia.org/wiki/File:Benzene_Ouroboros.png

"In 1987 Koza was on an airplane, returning to California from an AI conference in Italy, when he had the crucial insight ... Koza was 30,000 feet above Greenland when he asked himself why a genetic algorithm, so adept at refining pipelines, couldn't be used to evolve its own software." Popular Science, April 2006.

http://www.popsci.com/scitech/article/2006-04/john-koza-has-built-invention-machine

It is easy to imagine that viewing Greenland's rugged terrain below through a porthole might well have set off ideas about algorithms for traversing "fitness landscapes", but does this moment in summer 1987 represent the birthday of what we now call GP? More important, does GP have a single identifiable starting point at all?

This goes to the root of the question of whether our appetite for dramatic moments of inspiration distorts our understanding of scientific advance. Many historians of science and some scientists have argued that scientific innovation is generally a much more cumulative process than depicted in our memorable myths. The prevalence of priority disputes (Merton, 1957) suggests that sudden breakthrough by an individual genius is not in fact the norm. Indeed Merton (1961) has argued that "multiples", i.e. near-simultaneous discoveries by unconnected researchers, are more normal.

Returning to Mendeleev, for example, Eric Scerri (1998) has raised this point in connection with the periodic table (or "system") of chemical elements.



Photo credit - Stig Nygaard: https://www.flickr.com/photos/stignygaard/448189871/sizes/o/

"The discovery of the periodic system for classifying the elements represents the culmination of a number of scientific developments, rather than a sudden brainstorm on the part of one individual. Yet historians typically consider one event as marking the formal birth of the modern periodic table: on February 17, 1869, a Russian professor of chemistry, Dimitri Ivanovich Mendeleev, completed the first of his numerous periodic charts." -- Scerri, E., 1998, p. 78.

An elegant statement of the polarity from Eureka moment to incremental innovation is made by Gunther Stent (1972), with reference to real genetics rather than simulated genes inside a computer.

"I believe that if Watson and Crick had not existed, the insights they provided in one single package would have come out much more gradually over a period of many months or years. Dr. B might have seen that DNA is a double-strand helix, and Dr. C might later have recognized the hydrogen bonding between the strands. Dr. D later yet might have proposed a complementary purine-pyrimidine bonding, with Dr. E in a subsequent paper proposing the specific adenine-thymine and guanine-cytosine nucleotide pairs. Finally, we might have had to wait for Dr. G to propose the replication mechanism of DNA based on the complementary nature of the two strands. All the while Drs. H, I, J, K and L would have been confusing the issue by publishing incorrect structures and proposals." Gunther S. Stent (1972). Scientific American, 227, p. 90.

In my view, this is a realistic summary of the point at issue (although I would want to bestow the title of Professor on Drs. H, I, J, K and L). Clearly Stent accepts that scientific advance can proceed either by sudden large leaps or in gradual small steps. In the rest of this article, I will take this as given, and examine where GP falls along this polarity, and in so doing develop a simple method which I propose can be employed to elucidate the trajectories of other cases of scientific or technical innovation.

From Idea to Implementation

As might be expected there was a delay between having the concept of GP and embodying that concept in executable computer code. The basic idea of having a computer somehow evolve its own programs is known to have occurred to several people in the years since Turing (1948) wrote of evolutionary search as a route to machine intelligence.

"There is the genetical or evolutionary search by which a combination of genes is looked for, the criterion being the survival value" -- Turing (1948) p. 16. http://www.alanturing.net/turing_archive/archive/l/l32/L32-019.html

Ironically, this report was dismissed as a "schoolboy essay" by none other than Charles Darwin (Copeland, 2012) and remained unpublished until 1969 (Meltzer & Michie, 1969). The Darwin who

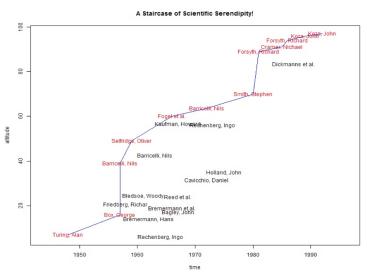
regarded Turing's ideas on evolutionary search as unworthy of publication was Turing's superior at the National Physical Laboratory, Sir Charles Galton Darwin, grandson of the great naturalist. However, the basic idea behind GP did find its way into print several times before Koza's 1987 flight over Greenland.

- "The scheme sketched is really a natural selection on the processing demons. If they serve a useful function they survive, and perhaps are even the source for other subdemons who are themselves judged on their merits." -- Selfridge, O. (1959). p. 14.
- "...the generation procedure operates in parallel fashion, producing sets or populations of programs" -- Holland, J.H. (1962). p. 298.
- "symbioorganisms will consist of numbers, and numbers in the machine can be interpreted as instructions according to any arbitrary code which can be established by writing an interpretive program." -- Barricelli, N. (1963). p. 2.
- "Thus, nonregressive evolution proceeds to find better and better programs for attacking the problem in hand." -- Fogel, L., Owens & Walsh (1966). p. 12.
- "...this highlights the fact that the rules are really programs in a special-purpose language, which might lead to the conclusion that the system should ultimately generate LISP functions." -- Forsyth, R. (1981). p. 165.

Thus the conceptual ingredients of what became GP were "in the air" for many years before it was put into practice. This article, however, concentrates not so much on the concept as on its implementation in working software, on the principle that the Wright brothers rather than Leonardo da Vinci are generally recognized as the first to launch powered heavier than air flying. (Actually, they are not universally recognized: the history of powered flight turns out on investigation to be more a case of many small hops than one grand take-off, but that's another story.)

The Ascent of GP

I am not a historian of science, nor indeed a historian of any kind. However, address at the EvoStar Conference in Porto in March 2016, I felt it incumbent upon me to do some historical investigation, if only to clarify my position in the story of GP. It was clear that I had been invited as a voice from the early pioneering days of GP, on the basis of being the author of BEAGLE, a rule-finder inspired by Darwinian principles (Forsyth, 1981). The justification for inviting me to stand up in front of 200 researchers knowledgeable about evolutionary computing was the notion that BEAGLE



was arguably the first working GP system. Informally, I had occasionally made that claim myself, but would it stand up to serious scrutiny?

Oddly enough, there doesn't seem to be a generally agreed "scientific" way of settling priority questions in science. So I devised my own framework. Readers can judge its strengths and weaknesses from what follows. But this is not a detective mystery, so let's start by spoiling the punchline and revealing the result. Below is a graph depicting the ascent of GP from 1948 (when it was just a glint in Alan Turing's fertile imagination) to 1992 (when Koza's 819-page tome presented the world with what amounted to a mature technology).

This plot shows 25 names positioned on 2 axes. The names are authors of papers or reports describing evolutionary computing systems which possessed attributes we now consider distinctive of GP systems. (Actually, 24 of the papers describe working systems, one (Turing, 1948), is included out of respect and as an initial benchmark, since although it prefigures the entire field it doesn't describe a working program.)

The horizontal axis, time, is relatively straightforward: it is the year when the paper or report was published (except Turing's, dated when it was written). The vertical axis is named "altitude", alluding among other things to that famous flight over Greenland. It requires further explanation (below).

The hues, red or black, depend on whether the position (of the middle of the name) lies on the efficient or Pareto frontier, indicated by the blue connecting line. A point lies on this frontier if no other point is both earlier and higher in altitude. This division into positions on and off the efficient frontier inevitably does carry evaluative implications, so its basis needs to be made explicit, as will be attempted shortly. One caveat that should be made immediately is that none of these published researchers were engaged in a "contest" to score a high altitude rating. They were describing findings and explaining methods to fellow workers in their fields. In other words, even if we equate altitude on this graph with proximity to full-fledged modern GP, that is not what most of them were trying to achieve. To avoid misinterpretation, it should be stressed that a point lower on this graph could well have more value as a contribution to the development of evolutionary computation -- in some respects -- than a higher point, even if we accept that the graph is valid within its terms of reference.

A Spreadsheet of Serendipity

The graph above required me to track down and read more than 25 articles of potential relevance to the development of GP. In this task I took books by Goldberg (1989) and Fogel (1998) as well as William Langdon's Genetic Programming Bibliography (http://www.cs.bham.ac.uk/~wbl/biblio/) as my starting points. To assess whether, or more accurately to what degree, an article described a GP system required compiling a list of defining or distinctive attributes of GP systems. To compile this list I began with the definition given by Bäck et al. (1997), quoted earlier, as well the distinctive features listed by Kinnear (1994):

- Tree-structured heritable material
- Variable-length heritable material
- Executable heritable material
- Syntax-aware crossover

I added the stipulations that the article should describe a working computer system and that it should have an obvious Darwinian or evolutionary basis. However, it soon became apparent that I was not going to find a clear-cut short list of necessary and sufficient conditions to determine conclusively whether an article described a GP system or not. This prompted me to settle on a weighted-sum model. This involved 12 features, weighted according to their perceived importance, including the four from Kinnear (1994) above, which between them accounted for 60% of the total weighting. The full list, with weightings, can be seen in the Appendix.

These weighted features then became columns in a simple spreadsheet where the rows represented the 25 articles selected, ordered by publication year. The spreadsheet can be accessed at http://www.richardsandesforsyth.net/software/ by anyone who wants to look at the details or experiment with differing assumptions, such as altered weights or additional/alternative attributes. (Save GPsheet.xlsx from the above location.)

All that remained to be done was to fill in the cells of this grid, i.e. to decide whether or not (1 or 0) the system concerned exhibited the attribute in question. If you obtain the spreadsheet, you will see that 30 of the 300 cells contain the number 0.5, meaning that in 10 percent of these supposedly binary decisions I was unable to make a firm judgement. This isn't wholly due to lack of decisiveness or understanding on my part; rather it underlines the influence of John Koza. Since the influential books by Koza (1992; 1994), a kind of template for describing systems of this nature in print has become customary. But earlier researchers weren't working with shared assumptions that in describing a GP system one would normally record explicitly the mode of crossover, the rate of mutation, the number of generations, the allowable operators and so on. Even parameters like population size were not always made explicit.

Thus, to the extent to which my choice of attributes, weightings and the rest is reasonable (which remains to be further discussed), this simple spreadsheet gives us a perspective on the development of an important subfield of computer science. This perspective does not force us to pick a single Eureka moment as the definitive start date. It gives us a more nuanced view; indeed a view from several angles, so to speak, since it is possible to adjust many of the parameters involved to observe their effects on the overall picture.

When it comes to the matter of assigning credit for discoveries, the efficient frontier does provide relevant information. I think it does make sense to regard the researchers on the efficient frontier as contributors to the main line of development of GP. It shows that GP arose from a process involving 12 particularly significant contributions by 11 researchers (nine authors and two co-authors). I suspect this is a worthwhile corrective to the mythic view of the solitary genius receiving a bolt of mystical inspiration. As long as we remember that the points off the efficient frontier are not failures but may themselves be contributions to a different line of development, we will not be tempted to make a simplistic division into sheep versus goats.

As regards the issue of small steps versus large leaps, some might feel tempted to note that the biggest jump on the graph shown above is associated with Barricelli (1957) and the second biggest with Forsyth (1981); but doing so is surely placing more weight on the assumptions behind the model than they can sensibly bear.

Limitations

It is fair to point out that this exercise has several limitations. In the first place, it relies heavily on my individual judgement. Human judgement is a fine and necessary thing, but it is well attested (see, for instance, Kahneman, 2011) that it is vulnerable to bias and prejudice. Multi-person judgement, if it can be elicited in conditions designed to minimize the chance of "groupthink", is usually more reliable than that of a single individual. Thus it would help if more people were involved. This is perfectly possible in principle. In high-stakes cases the same sort of study could be arranged to deliver more reliable results, with the author-by-attribute grid combining many experts' judgements. It is essentially a question of time and effort. In the present instance, I had the motivation to put some time in, and a participant's point of view, which has advantages as well as drawbacks.

The attributes chosen in this instance are open to challenge, as are their weightings. Here again, involving more people would help. It is easy to envisage a panel of experts debating such choices until a consensus emerges. Again this is a matter of resources, rather than a flaw inherent in the method. In the present case, the worksheet is public and open to amendment. It provides a framework for debate.

There is also the need to guard against forming a misleading impression from the efficient frontier of some sort of unbroken single mainstream. It not a pedigree chart or even a relay where a baton is passed from hand to hand. It does not imply that, for instance, Barricelli (1972) had read Fogel et al. (1966), or that Fogel et al. knew of the work of Selfridge (1959). Even a perusal of citations would not establish that conclusively. It merely links papers that, in a sense, made an unanticipated advance towards modern GP, or, strictly speaking, towards GP as defined by a particular set of characteristics. In addition, there is always the possibility that (for example) a ground-breaking paper in Russian or Japanese from the 1960s which has languished unread by the English-speaking world could be rediscovered and change the whole shape of the progress chart shown above. This merely means that any conclusions reached from this study remain provisional. The more people involved in an exercise such as this, the less likely it would be that a major contribution was overlooked, thus the more credibility that could be attached to its findings.

Finally, the article by Dickmanns et al. (1987) is in German and my grasp of German is exceedingly tenuous. I would be grateful if a German-speaker could check and revise that row of the spreadsheet. More generally, if anyone wants to help improve this spreadsheet, currently hosted at http://www.richardsandesforsyth.net/docs.html, please feel free to contact me. Ideally it could be hosted on a public forum and become a crowd-sourced repository of consensus opinion on this topic. I would be interested in hearing from anyone who wants to work towards such an objective.

Conclusion

This article has presented a pilot study, limited in scope. Its specific conclusions are open to various challenges and therefore highly tentative. Nevertheless, it introduces what I believe to be a novel but readily intelligible technique for approaching the vexed question of academic priority. With more resources, and appropriate amendments, this technique could be applied to shed light on the important, and often contentious, subject of innovation in a variety of scientific and technical fields.

Acknowledgement

I would like to thank Dr James McDermott for making helpful suggestions for improving an earlier draft of this article.

Declaration of Interest: The foregoing describes a piece of small-scale curiosity-driven research, not free from individual bias. As will have become apparent, I have a personal interest in rescuing BEAGLE (Forsyth, 1981) from oblivion. Hence my motivation for writing the present article. Nevertheless I have endeavoured to take a relatively dispassionate view of the topic.

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Appendix

The table below describes the attributes used to characterize each contribution to the development of GP. It also gives the attributes' weightings as in the spreadsheet used to give the 2-dimensional plot shown above. The score labelled "altitude" on the vertical axis of that plot was computed as a weighted sum

$$Ai = Di \times \Sigma(Wj \times Cij)$$

where Ai is the altitude score of item i, Cij is 0 or 1 (occasionally 0.5) indicating whether characteristic j belongs to item i and Wj is the weighting assigned to characteristic j. Di acts as a gatekeeper: it is the 0/1 score on the first attribute, "Clear Darwinian Basis", which is treated exceptionally. Ideally this should be 1 for every row in the worksheet, since if the paper concerned didn't employ an evolutionary approach, it would be discussing some other kind of optimization. In theory, therefore, it should be redundant. However, there was a borderline case (Friedberg, 1958) which received 0.5 on this attribute.

It will be seen that the first five attributes are dominant: the first acts as a switch, the next four contribute 60% of the total weighting.

Attribute	Weight	Description
Clear Darwinian basis	*	1 if the system uses an analogue of evolution by natural selection (0.5 in doubtful case)
Variable-length heritable material	15	1 if the structures being evolved can vary in length, zero otherwise
Tree-structured heritable material	20	1 if the structures being evolved have a tree-like form, zero otherwise
Syntax-aware crossover	10	1 if the crossover operator must know how to slice the structures being evolved at syntactically appropriate boundaries, zero if it operates blindly
Population members executable as programs	25	1 if the structures being evolved are executable expressions, zero otherwise
Population size exceeds two	10	1 if the size of the population of structures being evolved is 3 or more, zero otherwise (some early systems used tiny populations)
Uses crossover operation	5	1 if the system employs crossing of 2 or more parental structures to create novel structures, zero if mutation of only a single parent is used ('sexual' versus 'asexual' reproduction)
Uses mutation operator	2	1 if mutation (some kind of random change) is used in generating new structures, zero otherwise
Export of executable software	5	1 if the structures generated can be exported as software to be executed externally from the generating system, zero otherwise
Genotypes incorporate looping	2	if the structures being evolved can express a fundamental programming construct, namely repetition of a section, zero otherwise
Explicit submodule generation	2	1 if the structures being evolved can incorporate another fundamental programming construct, namely a generated subroutine, zero otherwise
System applied by others than originator	2	1 if the generating system was used by others, zero if it was only used by its originator
Selection at topmost level	2	1 if the system used the so-called "Pittsburgh" approach, in which the whole structure is subject to evolutionary optimization; zero if it used the so-called "Michigan" approach, in which only some portions of an overall structure are subject to evolutionary optimization

Note: As mentioned earlier, in cases of doubt, some papers were given a rating of 0.5 on some of these supposedly binary attributes.

Richard Forsyth is a relic from an earlier phase of evolutionary computing. In 1981, inspired by even earlier pioneers like Oliver Selfridge and Gordon Pask, he published an account of what was arguably the first working example of tree-structured program code optimized by evolutionary methods. Nowadays it would probably be called Genetic Programming. At the time he called it a Darwinian rule-learner trained by "naturalistic" selection". The term didn't catch on. In 1985 he started selling a PC version of the BEAGLE rule-finder system (Biological Evolutionary Algorithm Generating Logical Expressions). Fortunately his lack of business acumen spared him from the fate of becoming a software billionaire. In consequence, he has spent much of the last 30 years on a zigzag path through an assortment of institutions in Britain's "higher" education system. Released from the academic treadmill, he has recently revived & revised BEAGLE. which is freely available under the GNU licence, along with a companion system named RUNSTER (Regression Using Naturalistic Selection to Evolve Rules), on his website: http://www.richardsandesforsyth.net/beagling.html.



PPSN 2016: 14th International Conference on Parallel Problem Solving from Nature

Review by Anna Esparcia

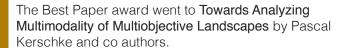
PROS Research Centre, Universitat Politècnica de València, Spain

The 14th International Conference on Parallel Problem Solving from Nature was held in Scotland's capital city, Edinburgh, from September 17th to the 21st. PPSN is a medium-sized conference (152 registered participants) where emphasis is on exchange of ideas among participants; this is achieved by the poster sessions, in which authors and their audiences can interact in an open and informal manner.



As is customary in PPSN, the first two days were devoted to workshops and tutorials. The 16 tutorials covered a wide range of topics, from more traditional ones like multiobjective optimisation to new subjects like Smart Cities, EAs in the Cloud and Cryptography, and old favourites with new practical approaches, such as Evolutionary Robotics. The four workshops covered both applied and more theoretical aspects.

The regular conference consisted of 93 poster presentations corresponding to full papers accepted, out of 224 submissions (41.5% acceptance rate). Keynote speakers Susan Stepney, Josh Bongard and late addition Andy Philippides provided insights in areas as varied as open endedness in simulation, crowdsourcing humans and machines for solving complex problems, and the navigation powers of ants.



The social aspects consisted a double decker bus tour of historic Edinburgh and a conference dinner, including traditional Scottish music sung by the organisers themselves.

Warm congrats to co-chairs Emma Hart and Ben Paechter, and Local Chair Neil Urquhart for a successful conference! Photos from the conference can be found at: https://goo.gl/photos/Jc88NaKj1BxZ9f2M8

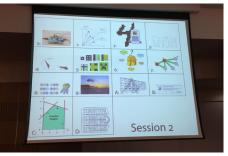






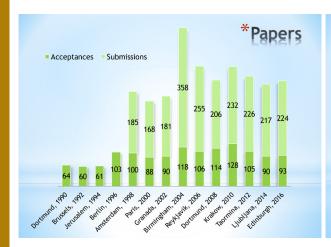


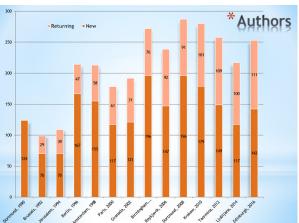


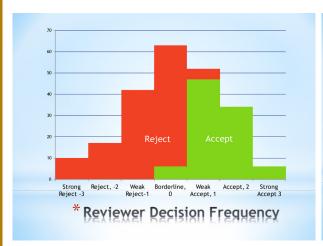


PPSN 2016 statistics

The following data is provided by Gabriela Ochoa, Nadarajen Veerapen and Fabio Daolio, of the University of Stirling.





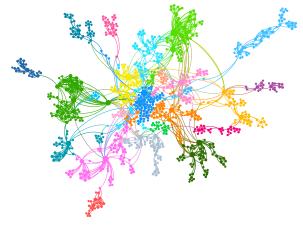






No. of authors 1934 No. of papers 1324 Papers per author Avg = 1.8, Max = 24Avg = 2.6 , Max = 14 44 Authors per paper Collaborators Avg = 3.6, Max = 41Largest component 959, 49.6% Distance Avg = 6.2, Max = 17Clustering Coeff.

Network of PPSN Collaborations



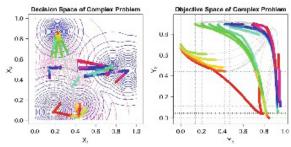
The network shows author collaborations from the entire PPSN history. An interactive graph that shows all authors by name can be explored here.

PPSN 2016 Best paper award

Towards Analyzing Multimodality of Multiobjective Landscapes

Pascal Kerschke, Hao Wang, Mike Preuss, Christian Grimme, André Deutz, Heike Trautmann and Michael Emmerich

This paper formally defines multimodality in multiobjective optimization (MO). We introduce a test-bed in which multimodal MO problems with known properties can be constructed as well as numerical characteristics of the resulting landscape. Gradient- and local search based strategies are compared on exemplary problems together with specific performance indicators in the multimodal MO setting. By this means the foundation for Exploratory Landscape Analysis in MO is provided.



Local Pareto fronts for a complex mixed sphere problem consisting of five peaks per objective, resulting in a total of 30 disconnected



Keynote speaker

The PPSN team was very sorry that Dr Kate Bentley from Harvard Medical School was unable to attend PPSN due to personal circumstances. However, they were delighted that Dr Andy Philippides was able to stand in at very short notice. Andy delivered a fascinating talk that engaged everyone in the audience – thank you Andy!

Navigation with a tiny brain: getting home without knowing where you are

Andrew Philippides, University of Sussex, Brighton, UK

Abstract

The use of visual information for navigation is a universal strategy for sighted animals, amongst whom social insects are particular experts. The general interest in studies of insect navigation is in part due to their small brains; biomimetic engineers can take inspiration from elegant and parsimonious control solutions, while



biologists look for a description of the minimal cognitive requirements for complex spatial behaviours. We take an interdisciplinary approach to studying visual guided navigation by combining behavioural experiments with modelling and robotics to understand how complex behaviour can emerge from the combination of a simple sensory system and brain, interacting with innate behaviours all tuned to the natural habitat. In so doing, we show that an agent can robustly navigate without ever knowing where it is, without specifying when or what it should learn, nor requiring it to recognise specific objects, places routes or maps. This leads to an algorithm in which navigation is driven by familiarity detection rather than explicit recall, with sensory data specifying actions not locations. Route navigation is thus recast as a search for familiar views, allowing an agent to encode routes through visually complex worlds in a single layer neural network after a single training run. We suggest that this work is a specific example of a more general idea which has implications for engineers seeking nature-inspired solutions: By considering how animals directly acquire and use task-specific information through specialised sensors, brains and behaviours, we can solve complex problems without complex processing.

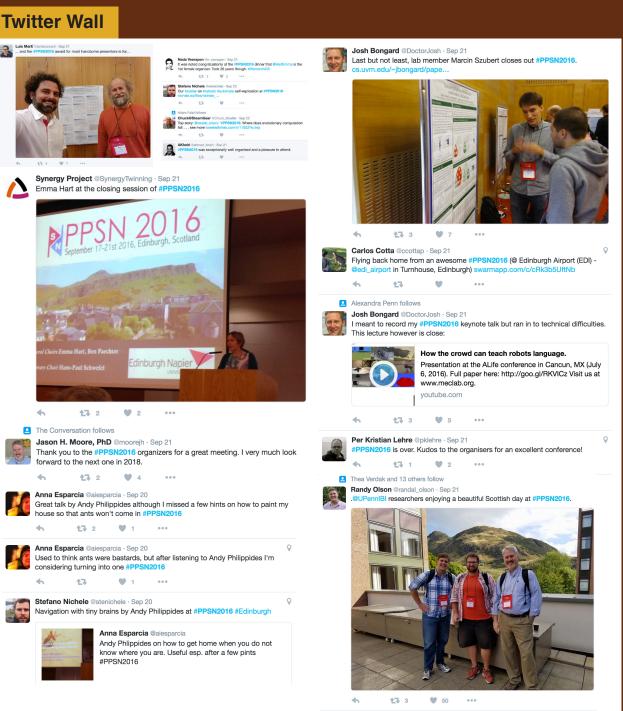
Biography

Andrew Philippides is a Reader in the Department of Informatics at the University of Sussex and co-director of the Centre for Computational Neuroscience and Robotics (http://www.sussex.ac.uk/ccnr/). Having read Mathematics at King's College Cambridge, he moved to Sussex to do an MSc in Artificial Intelligence and Adaptive Systems followed by a doctorate in Computational Neuroscience and Robotics, and has been at Sussex since. His research is interdisciplinary and is best described as computational neuroethology; That is, he combines behavioural experiments with computational and robotic models to zunderstand, and take inspiration from, biological systems. Current research topics include: visual navigation in insects and robots, neuromodulation in (real and artificial) neural networks, analysis of biological imaging data



and agent-based modelling applied to crowd movement and human migration.





Fun and Games at IEEE WCCI 2016, Vancouver, Canada

W. B. Langdon, University College London

Following UCL spin-out DeepMind's success at beating the world Go champion, there was very much a flavour of artificial intelligence (AI) in the air. For example Deep Learning was the topic of Juergen Schmidhuber's invited plenary talk and some of the competitions, for example, Diego Perez and Simon Lucas' General Video Game AI Competition (winner Tom Vodopivec shown in Figure 9). David Fogel president of Natural Selection Inc., gave an impressive lecture open to the general public (see Figure 1). He covered the story of how he and Kumar Chellapilla evolved a competition level checkers (draughts) player. He talked about taking it out into the real world to play people in online competitions. He related the difference in his opponents online behaviour when playing as David 1101 or when playing as Blondie242.



The AI Big Data theme continued the next day with Una-May O'Reilly's invited plenary talk for CEC (see Figure 2). Dr. O'Reilly founded the AnyScale Learning For All (ALFA) group in MIT's Computer Science and AI Laboratory. Her theme was "The world is raining data" and how evolutionary computation (particularly genetic programming [9]) has been made, using cloud computing resources, to scale to cope with Big Data. (Her working definition of Big Data is datasets that are too big to fit into your personal computer, be it laptop or desktop, so you need cloud scale computing.) Una-May stressed the importance of GP's ability to automatically created comprehensible non-linear models and how over the last five years she made it fast enough to compete with other machine learning (AI) techniques. She also described the work of some of her collaborators and how they (and potential you) can use the ALFA FlexGP cloud infrastructure to hook up other techniques. Thus allowing easy comparison of your technique with other techniques and ready collaboration with other researchers.

Professor Yun Li, of the School of Engineering, Glasgow University, UK, headed a nice workshop on Key Challenges and Future Directions of Evolutionary Computation. It started with presentations by Drs. Yi Mei and Bing Xue of Victoria University of Wellington, New Zealand, me (Figure 3) and Dr. Abhishek Gupta of Rolls-Royce@NTU, Nanyang Technological University, Singapore. In the second section Prof. Li broke the audience into four groups lead by: Xin Yao, Carlos Coello Coello, Yuhui Shi and Gary Fogel. I found the applications quadrant very interesting. Prof. Li plans to publish the findings of the workshop.

Following the IEEE computational intelligence society award banquet on Wednesday evening (see Figure 4) Professor Graham Kendall (Vice-Provost at the University of Nottingham's Malaysia campus) gave the invited plenary talk for CEC on "Is Evolutionary Computing Evolving Fast Enough?" At first I misinterpreted the title to refer to the speed of GA runs and was thinking along parallel computing lines. However I think Prof. Kendall's concern was that other parts of AI, particularly AlphaGo, had recently had gained much notoriety and press coverage and so EC was not shining as it aught. Nonetheless I was struck by the number of times Graham mentioned research other than his own, particularly GP's ability to automatically repair software bugs [7] (for which Stephanie Forrest won the 2009 Gold Humie) and the recent work on Genetic Improvement [5]. He mentioned Professor Mark Harman of UCL, who had scoped two Humies the week before at GECCO, several times.

In addition to the several hundred sessions and formal events, one should not overlook the numerous social activities (see Figures 5 to 9). WCCI included several coffee breaks per day (sometimes including ice cream). I was impressed with the convention centre's ability to serve coffee/tea/pasteries etc. to everyone immediately when the keynotes in the huge west ballroom ended. In addition to informal discussions over coffee, meal breaks (particularly the well timed lunch gap in the busy schedule) provided opportunities to meet old acquaintances and make new friends. Sometimes close by the convention centre (e.g. next to the killer whale see Figure 6)

¹ DeepMind and its deep learning tool AlphaGo is now owned by Google.

² Dave's book [3] was reviewed by Daryl Essam in Genetic Programming and Evolvable Machines [2].



Fig 1: David Fogel just about to start his public lecture



Fig 2: Una-May O'Reilly invited CEC plenary speaker

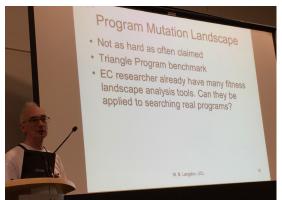


Fig 3: The author presenting [6] at the Key Challenges and Future Directions of Evolutionary Computation workshop.

and sometimes further a field. WCCI was right in centre of the Vancouver on the north shore of the peninsular facing Vancouver harbour (Figure 7). So right by the shopping area with lots of good and not so expensive places to eat and still have time to return on foot for the start of the afternoon plenaries.

Whilst neural networks networks have at last begun to show some return for the faith early Al pioneers placed in them, we in EC should feel too down hearted. As Blondie24 (page 1) showed more than a decade ago, you can evolve game playing Al far in excess of your own abilities. When I started in GP, it was claimed that it would never be able to evolve a real program like a text editor. Yet this year's Gold Humie winner Alexandru Marginean has shown GP can evolve a human written editor (namely Kate) by automatically grafting into it new functionality borrowed from open source C++ web sites [8].

To conclude. WCCI remains a huge conference. The emphasis on size means sometimes papers are of variable quality. This time there was very much an up beat flavour. A feeling that AI was coming good. Monte Carlo Tree Search is still popular but is being adapted or replaced by deep learning techniques such as Juergen Schmidhuber's (page 1) LSTM. Competitions, such as Simon Lucas' multiple video games, continue to be vibrant and offer EC AI challenges. Despite the arrival of NSGA-III and other multi- objective techniques, NSGA-II [1] is still popular. Although Big Data (page 1) was "in the air", in practise people are still using "small data" (even the misused Pima dataset [4, Fig. 1]). Of the many interesting papers, some stand out, such as: regularizing GP using "vanishing ideal" functions (Kera and Iba), better ways to deal with "missing data" (Tran et al.) and Bi-level optimisation BIOP (Gupta et al.) as a way of combining GP and GAs. Perhaps some of these, or indeed your own, will take up O'Reilly's scalable GP offer (page 1)? On a personal note, it was gratifying to hear the UCL CREST group's work, particularly on genetic improvement, widely discussed.



Fig 4: After the conference banquet Vancouver staged one heat in its festival of lights in English Bay. Here is part of the Australian competition entry.



Fig 5: Dr. Dipti Srinivasan (chair of student activities at WCCI, National University of Singapore), Prof. Dr. Julia Chung (vice president IEEE Computational Intelligence Society (CIS), National Cheng Kung University, Taiwan), Dr. Valerie Cross (Miami University, Oxford, Ohio, USA), Prof. Dr. Sanaz Mostaghim (chair of CEC, Otto von Guericke University, Germany), Dr. Keeley Crockett (chair of student activities for the IEEE CIS, Manchester Metropolitan University, UK).

³ The proceedings came on a USB memory stick. It contains about 14000 pages, which if printed out would weigh 32 Kg (about the weight of a ten year old child).



Fig 6: Douglas Coupland's 25 foot tall Digital Whale (2009) is right next to the Convention Centre.



Fig 7: View of the airport from the WCCI venue. Vancouver harbour is the world's busiest sea plane airport. The little (up to 9 passengers) float planes took off and landed through out the conference.

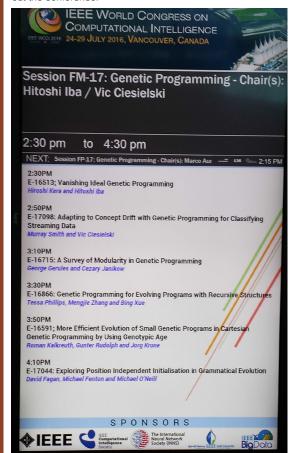


Fig 8: Outside each of the 30 plus seminar rooms there was an electronic display of the part of the 330 page time table showing exactly what was happening in the room in the current session.



Figure 9: Andrew J. Starkey (University of Essex), Tom Vodopivec (University of Ljubljana), Diego Perez (University of Essex), Anasol C. Pena Rios (University of Essex), Samineh Bagheri (Cologne University of Applied Sciences), Gonzalo Ruiz Garcia (University of Granada)

Acknowledgement

Many people contributed to interesting discussions, I would particularly like to thank David Fogel, Sanaz Mostaghim, Markus Wagner, George Gerules, Tom Vodopivec, Amir Gandomi, Bing Xue and Will Browne for their photographs. I saw a wonderful comment, so sadly not original: finally I would like to thank Canada for the beautiful city of Vancouver.

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EvoCOP

17th European Conference on Evolutionary Computation in Combinatorial Optimisation chairs: Bin Hu, Manuel López-Ibáñez **EvoMUSART**

6th International Conference on Evolutionary and Biologically Inspired Music, Sound, Art and Design chairs: Vic Ciesielski, João Correia





Amsterdam, The Netherlands. 19-21 April 2017 http://www.evostar.org

EuroGP 20th European Conference on Genetic Programming chairs: James McDermott, Mauro

chairs: James McDermott, Mar Castelli and Lukas Sekanina **EvoAPPLICATIONS**

20th International Conference on the Applications of Evolutionary Computation coordinator: Giovanni Squillero

Submission deadline 1 November 2016

Local Chair Evert Haasdijk Vrije Universiteit Amsterdam, The Netherlands Publicity Chair Pablo García-Sánchez University of Granada, Spain

Evo* coordinator Jennifer Willies

EVOSTAR 2017 TRACKS

EuroGP

20th European Conference on Genetic Programming

EVOCOP

The 17th European Conference on Evolutionary Computation in Combinatorial Optimisation

EvoMUSART

6th International Conference on Computational Intelligence in Music, Sound, Art and Design

EvoApplications

20th European Conference on the Applications of Evolutionary Computation

EvoBAFIN 2017

Natural Computing Methods in Business Analytics and Finance

EvoBIO 2017

Evolutionary Computation, Machine Learning and Data Mining for Biology and Medicine

EvoCOMNET 2017

Application of Nature-inspired Techniques for Communication Networks and other Parallel and Distributed Systems

EvoCOMPLEX

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Evolutionary Computation in Image Analysis, Signal Processing and Pattern Recognition

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Evolutionary Algorithms and Meta-heuristics in Stochastic and Dynamic Environments

EVOLUTIONARY COMPUTATION - JUST ACCEPTED

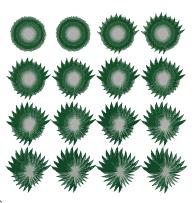
Problem Features vs. Algorithm Performance on Rugged Multi-objective Combinatorial Fitness Landscapes

Fabio Daolio, Arnaud Liefooghe, Sébastien Verel, Hernán Aguirre, Kiyoshi Tanaka

Abstract

In this paper, we attempt to understand and to contrast the impact of performance of randomized search heuristics for black-box multiobjective combinatorial optimization problems. At first, we measure the performance of two conventional dominance-based approaches with unbounded archive on a benchmark of enumerable binary optimization problems with tunable ruggedness, objective space dimension, and objective correlation (pMNK-landscapes). Precisely, we investigate the expected runtime required by a global evolutionary optimization algorithm with an ergodic variation operator (GSEMO) and by a neighborhood-based local search heuristic (PLS), to identify a –approximation of the Pareto set. Then, we define a number of problem features characterizing the fitness landscape, and we study their intercorrelation and their association with algorithm runtime on the benchmark instances. At last, with a mixed-effects multi-linear regression we assess the individual and joint effect of problem features on the performance of both algorithms.





within and across the instance classes defined by benchmark parameters. Our analysis reveals further insights into the importance of ruggedness and multi-modality to characterize instance hardness for this family of multi-objective optimization problems and algorithms.

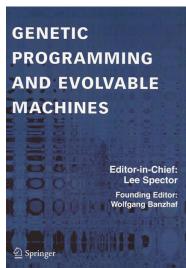
Full text: http://www.mitpressjournals.org/doi/pdf/10.1162/EVCO_a_00193

GENETIC PROGRAMMING AND EVOLVABLE MACHINES - ONLINE FIRST ARTICLES

Online Genetic Improvement on the java virtual machine with ECSELR Kwaku Yeboah-Antwi, Benoit Baudry

Abstract

Online Genetic Improvement embeds the ability to evolve and adapt inside a target software system enabling it to improve at runtime without any external dependencies or human intervention. We recently developed a general purpose tool enabling Online Genetic Improvement in software systems running on the java virtual machine. This tool, dubbed ECSELR, is embedded inside extant software systems at runtime, enabling such systems to self-improve and adapt autonomously online. We present this tool, describing its architecture and focusing on its design choices and possible uses.



Keywords

Genetic improvement, Evolutionary computation, Genetic programming, Artificial intelligence, Software engineering.

Full text: http://www.mitpressjournals.org/doi/pdf/10.1162/EVCO_a_00193

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Software: Are you are a developer of an EC software and you wish to tell us about it? Then, send us a short summary or a short tutorial of your software.

Lost Gems: Did you read an interesting EC paper that, in your opinion, did not receive enough attention or should be rediscovered? Then send us a page about it

Dissertations: We invite short summaries, around a page, of theses in EC-related areas that have been recently discussed and are available online.

Meetings Reports: Did you participate to an interesting EC-related event? Would you be willing to tell us about it? Then, send us a short summary, around half a page, about the event.

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